University of Ljubljana, Faculty of Computer and Information Science

Affective computing

Prof Dr Marko Robnik-Šikonja

Natural Language Processing, Edition 2026

Contents

- understanding emotions
- affective lexicons
- sentiment classification
- language specifics and cross-lingual approaches
- Related tasks: hate speech, offensive language, socially unacceptable speech

- Literature: Jurafsky and Martin, 3rd edition
- Some slides follow Jurafsky and Martin

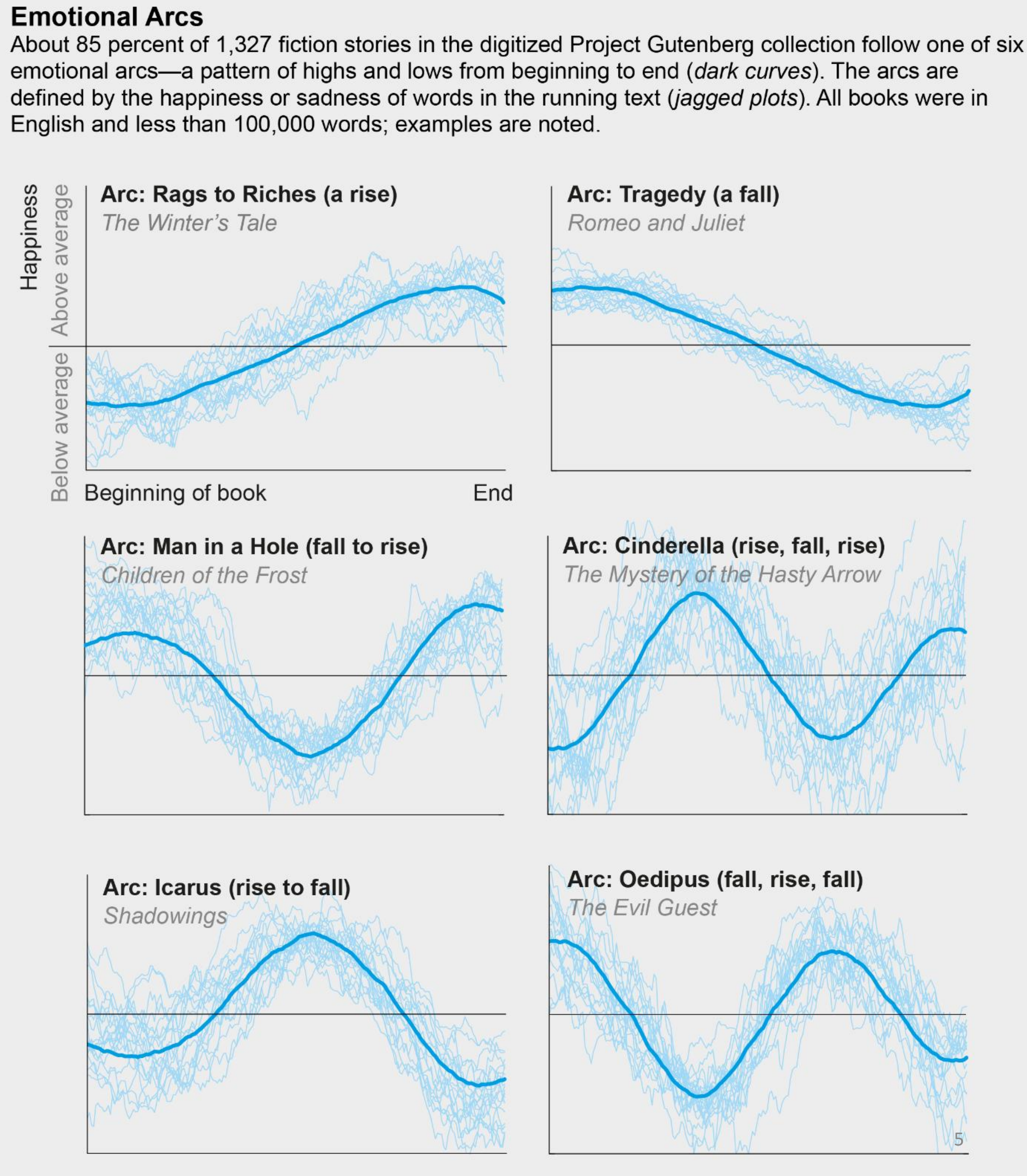
Affective meaning

- Drawing on literatures in
  - affective computing
  - linguistic subjectivity
  - social psychology
- Can we model the lexical semantics relevant to:
  - sentiment
  - emotion
  - personality
  - mood
  - attitudes

Why compute affective meaning?

- Detecting:
  - sentiment towards politicians, products, countries, ideas
  - frustration of callers to a help line
  - stress in drivers or pilots
  - depression and other medical conditions
  - confusion in students talking to e-tutors
  - emotions in novels (e.g., for studying groups that are feared over time)
- Could we generate:
  - emotions or moods for literacy tutors in the children's storybook domain
  - emotions or moods for computer games
  - personalities for dialogue systems to match the user

Example: emotional states of novels



Connotation in the lexicon

- Definition of connotation: an idea or feeling which a word invokes for a person in addition to its literal or primary meaning.
- An example: "the word ‘discipline’ has unhappy connotations of punishment and repression"

- Words have connotation as well as sense (i.e. additional “affective” dimension alike FrameNet)
- Can we build lexical resources that represent these connotations?
- And use them in these computational tasks?

Scherer's typology of affective states

- **Emotion**: relatively brief episode of synchronized response of all or most organismic subsystems in response to the evaluation of an event as being of major significance
  - **angry, sad, joyful, fearful, ashamed, proud, desperate**
- **Mood**: diffuse affect state …change in subjective feeling, of low intensity but relatively long duration, often without apparent cause
  - **cheerful, gloomy, irritable, listless, depressed, buoyant**
- **Interpersonal stance**: affective stance taken toward another person in a specific interaction, coloring the interpersonal exchange
  - **distant, cold, warm, supportive, contemptuous**
- **Attitudes**: relatively enduring, affectively colored beliefs, preferences predispositions towards objects or persons
  - **liking, loving, hating, valuing, desiring**
- **Personality traits**: emotionally laden, stable personality dispositions and behavior tendencies, typical for a person
  - **nervous, anxious, reckless, morose, hostile, envious, jealous**

Sentiment Lexicons

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The General Inquirer

Philip J. Stone, Dexter C Dunphy, Marshall S. Smith, Daniel M. Ogilvie. 1966. The General Inquirer: A Computer Approach to Content Analysis. MIT Press

- Home page: http://www.wjh.harvard.edu/~inquirer
- List of categories: http://www.wjh.harvard.edu/~inquirer/homecat.htm
- Spreadsheet: http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls
- Categories:
  - Positive (1915 words) and Negative (2291 words)
  - Strong vs Weak, Active vs Passive, Overstated versus Understated
  - Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation, etc.
- Free for research use

LIWC (Linguistic Inquiry and Word Count)

- 2300 words, >70 classes
- **Affective Processes**
  - negative emotion (*bad, weird, hate, problem, tough*)
  - positive emotion (*love, nice, sweet*)
- **Cognitive Processes**
  - Tentative (*maybe, perhaps, guess*), Inhibition (*block, constraint*)
- **Pronouns, Negation** (*no, never*), **Quantifiers** (*few, many*)
- commercial
- Home page: http://www.liwc.net/

Pennebaker, J.W., Booth, R.J., & Francis, M.E. (2007). Linguistic Inquiry and Word Count: LIWC 2007. Austin, TX

MPQA Subjectivity Cues Lexicon

Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. Proc. of HLT-EMNLP-2005.

Riloff and Wiebe (2003). Learning extraction patterns for subjective expressions. EMNLP-2003.

- Home page: http://www.cs.pitt.edu/mpqa/subj_lexicon.html
- 6,885 words
  - 2718 positive
  - 4912 negative
- Each word annotated for intensity (strong, weak)
- GNU GPL

Bing Liu Opinion Lexicon

Minqing Hu and Bing Liu. Mining and Summarizing Customer Reviews. ACM SIGKDD-2004.

- Bing Liu's Page on Opinion Mining
- http://www.cs.uic.edu/~liub/FBS/opinion-lexicon-English.rar

- 6786 words
  - 2006 positive
  - 4783 negative

SentiWordNet

Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. 2010 SENTIWORDNET 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining. LREC-2010

- Home page: http://sentiwordnet.isti.cnr.it/
- All WordNet synsets automatically annotated for degrees of positivity, negativity, and neutrality/objectiveness
- [estimable(J,3)] “may be computed or estimated”

```
Pos  0    Neg 0    Obj 1
```

- [estimable(J,1)] “deserving of respect or high regard”

```
Pos .75  Neg 0    Obj .25
```

Disagreements between polarity lexicons

Christopher Potts, Sentiment Tutorial, 2011

	Opinion Lexicon	General Inquirer	SentiWordNet	LIWC
MPQA	33/5402 **(0.6%)**	49/2867 **(2%)**	1127/4214 **(27%)**	12/363 **(3%)**
Opinion Lexicon		32/2411 **(1%)**	1004/3994 **(25%)**	9/403 **(2%)**
General Inquirer			520/2306 **(23%)**	1/204 **(0.5%)**
SentiWordNet				174/694 **(25%)**
LIWC				

Other Affective Lexicons

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Two families of theories of emotion

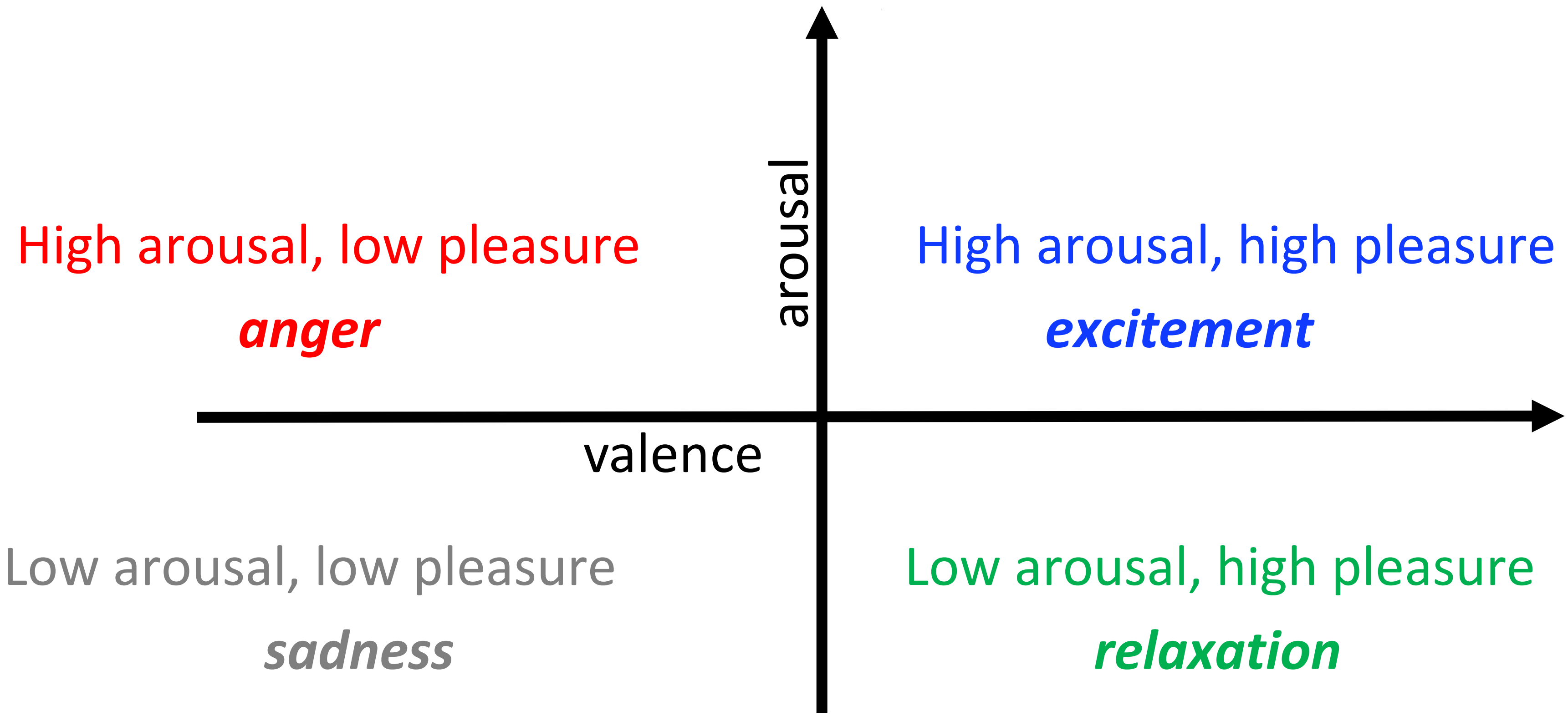
- Atomic basic emotions
  - A finite list of 6 or 8, from which others are generated
- Dimensions of emotion
  - Valence (positive, negative)
  - Arousal (strong, weak)
  - Control – dominance (in control, active vs. controlled, passive)

- Valence (psychology), also known as hedonic tone, is a characteristic of emotions that determines their emotional affect (intrinsic appeal or repulsion).

Ekman’s 6 basic emotions

Surprise, happiness, anger, fear, disgust, sadness

Valence/Arousal Dimensions



Atomic units vs. Dimensions

Distinctive

- Emotions are units.
- Limited number of basic emotions.
- Basic emotions are innate and universal

Dimensional

- Emotions are dimensions.
- Limited # of labels but unlimited number of emotions.
- Emotions are culturally learned.

Adapted from Julia Braverman

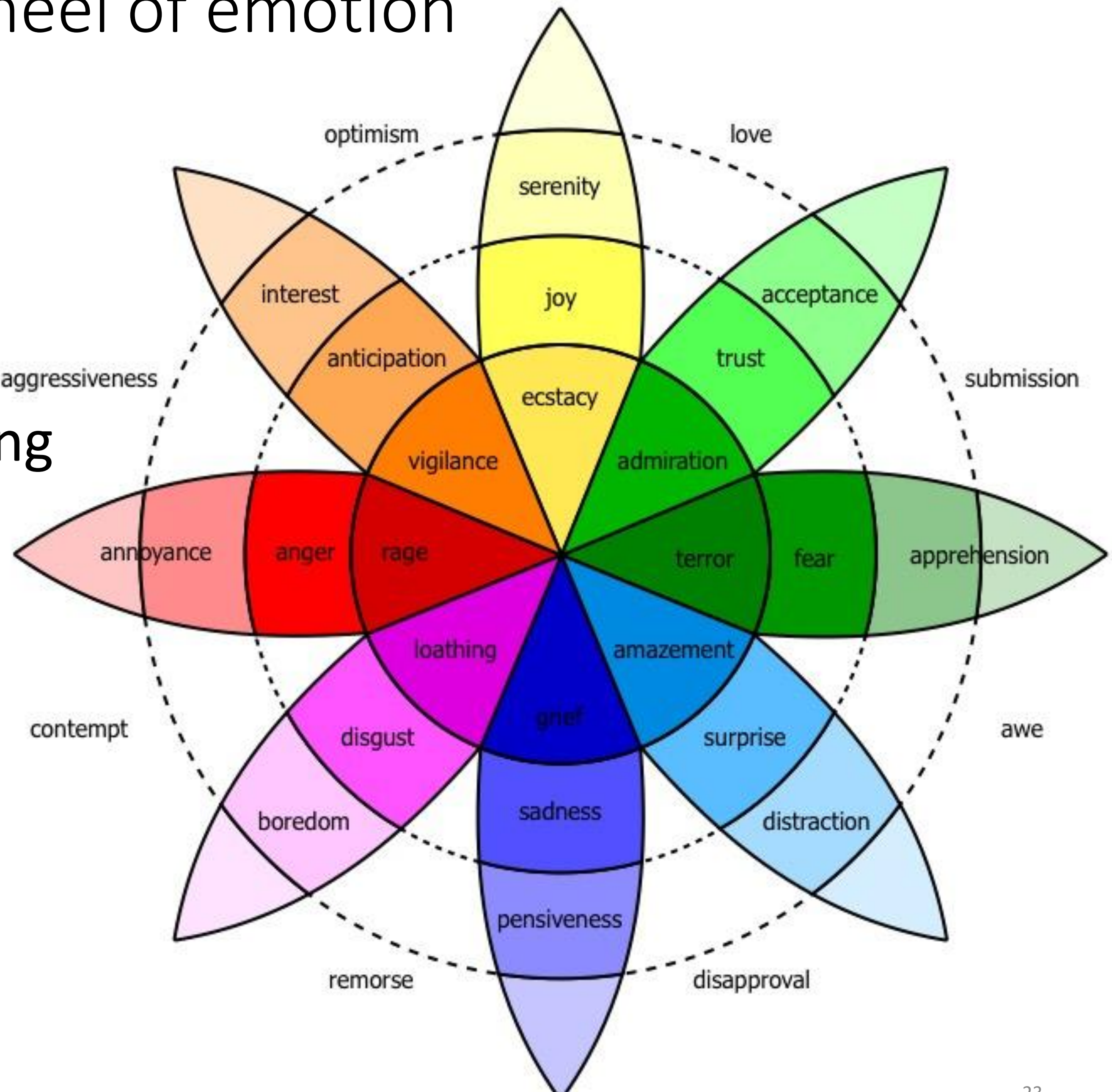
One emotion lexicon from each paradigm

1. 8 basic emotions:
    - NRC Word-Emotion Association Lexicon (Mohammad and Turney 2011)
2. Dimensions of valence/arousal/dominance
    - Warriner, A. B., **Kuperman**, V., and Brysbaert, M. (2013)

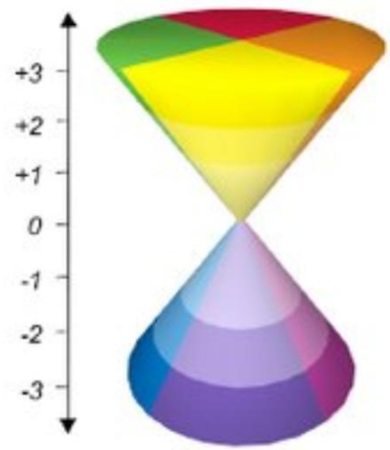
- Both built using Amazon Mechanical Turk

Plutchick's wheel of emotion

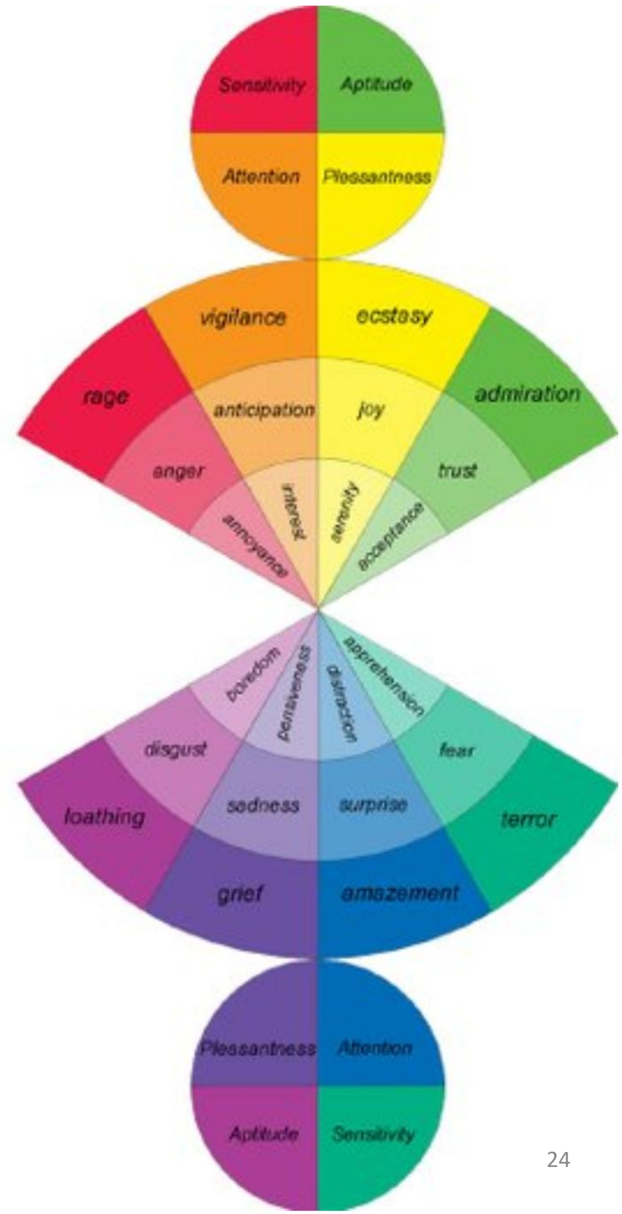
- 8 basic emotions
- in four opposing pairs
- joy–sadness
- anger–fear
- trust–disgust
- anticipation–surprise



Hourglass of emotion



	Pleasantness	Attention	Sensitivity	Aptitude
+3	ecstasy	vigilance	rage	admiration
+2	joy	anticipation	anger	trust
+1	serenity	interest	annoyance	acceptance
0	—	—	—	—
-1	pensiveness	distraction	apprehension	boredom
-2	sadness	surprise	fear	disgust
-3	grief	amazement	terror	loathing



NRC Word-Emotion Association Lexicon

Mohammad and Turney 2011

- 10,170 words chosen mainly from earlier lexicons
- Labeled by Amazon Mechanical Turk
- 5 Turkers per hit
- Give Turkers an idea of the relevant sense of the word
- Result:

```
amazingly   anger   0
amazingly   anticipation    0
amazingly   disgust 0
amazingly   fear    0
amazingly   joy 1
amazingly   sadness 0
amazingly   surprise    1
amazingly   trust   0
amazingly   negative    0
amazingly   positive    1
```

EmoLex	**# of terms**
EmoLex-Uni:	
Unigrams from Macquarie Thesaurus	
adjectives	200
adverbs	200
nouns	200
verbs	200
EmoLex-Bi:	
Bigrams from Macquarie Thesaurus	
adjectives	200
adverbs	187
nouns	200
verbs	200
EmoLex-GI:	
Terms from General Inquirer	
negative terms	2119
neutral terms	4226
positive terms	1787
EmoLex-WAL:	
Terms from WordNet Affect Lexicon	
anger terms	165
disgust terms	37
fear terms	100
joy terms	165
sadness terms	120
surprise terms	53
Union	**10170**

The AMT Hit

Prompt word: *startle*

Q1. Which word is closest in meaning (most related) to *startle*?

- *automobile*
- *shake*
- *honesty*
- *entertain*

Q2. How positive (good, praising) is the word *startle*?

- *startle* is not positive
- *startle* is weakly positive
- *startle* is moderately positive
- *startle* is strongly positive

Q3. How negative (bad, criticizing) is the word *startle*?

- *startle* is not negative
- *startle* is weakly negative
- *startle* is moderately negative
- *startle* is strongly negative

Q4. How much is *startle* associated with the emotion joy? (For example, *happy* and *fun* are strongly associated with joy.)

- *startle* is not associated with joy
- *startle* is weakly associated with joy
- *startle* is moderately associated with joy
- *startle* is strongly associated with joy

Q5. How much is *startle* associated with the emotion sadness? (For example, *failure* and *heart-break* are strongly associated with sadness.)

- *startle* is not associated with sadness
- *startle* is weakly associated with sadness
- *startle* is moderately associated with sadness
- *startle* is strongly associated with sadness

Q6. How much is *startle* associated with the emotion fear? (For example, *horror* and *scary* are strongly associated with fear.)

- Similar choices as in 4 and 5 above

Q7. How much is *startle* associated with the emotion anger? (For example, *rage* and *shouting* are strongly associated with anger.)

- Similar choices as in 4 and 5 above

Q8. How much is *startle* associated with the emotion trust? (For example, *faith* and *integrity* are strongly associated with trust.)

- Similar choices as in 4 and 5 above

...

Q9. How much is *startle* associated with the emotion disgust? (For example, *gross* and *cruelty* are strongly associated with disgust.)

- Similar choices as in 4 and 5 above

Lexicon of valence, arousal, and dominance

- Warriner, A. B., **Kuperman**, V., and Brysbaert, M. (2013). Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behavior Research Methods 45, 1191-1207.*

- **Ratings for 13,915 words for emotional dimensions:**
  - **valence** (the pleasantness of the stimulus)
  - **arousal** (the intensity of emotion provoked by the stimulus)
  - **dominance** (the degree of control exerted by the stimulus)

Lexicon of valence, arousal, and dominance

- **valence** (the pleasantness of the stimulus)
  9: happy, pleased, satisfied, contented, hopeful
  1: unhappy, annoyed, unsatisfied, melancholic, despaired, or bored
- **arousal** (the intensity of emotion provoked by the stimulus)
  9: stimulated, excited, frenzied, jittery, wide-awake, or aroused
  1: relaxed, calm, sluggish, dull, sleepy, or unaroused;
- **dominance** (the degree of control exerted by the stimulus)
  9: in control, influential, important, dominant, autonomous, or controlling
  1: controlled, influenced, cared-for, awed, submissive, or guided
- Again produced by AMT

Lexicon of valence, arousal, and dominance: Examples

Valence		Arousal		Dominance	
vacation	8.53	rampage	7.56	self	7.74
happy	8.47	tornado	7.45	incredible	7.74
whistle	5.7	zucchini	4.18	skillet	5.33
conscious	5.53	dressy	4.15	concur	5.29
torture	1.4	dull	1.67	earthquake	2.14

Learn word sentiment supervised by online review scores

Potts, Christopher. 2011. On the negativity of negation. SALT 20, 636-659.
Potts 2011 NSF Workshop talk.

- Review datasets
  - IMDB, Goodreads, Open Table, Amazon, Trip Advisor
- Each review has a score (1-5, 1-10, etc.)
- Just count how many times each word occurs with each score (and normalize)
- Lexicons are not really used anymore and the following example shows why not

Analyzing the polarity of each word in IMDB

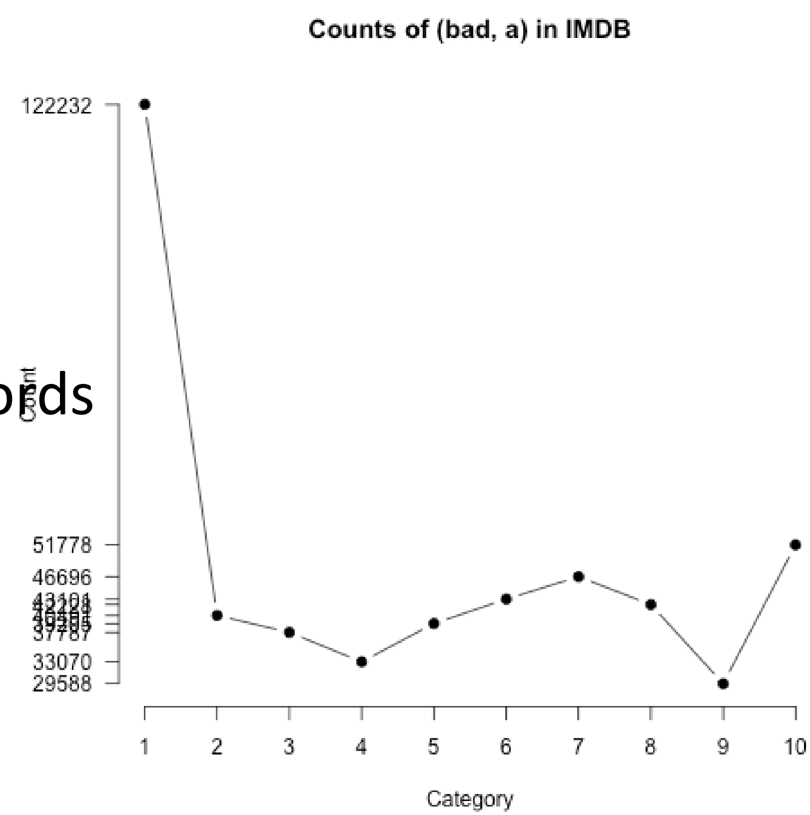
Potts, Christopher. 2011. On the negativity of negation. SALT 20, 636-659.

- How likely is each word to appear in each sentiment class?
- Count("bad") in 1-star, 2-star, 3-star, etc.
- But can't use raw counts:
- Instead, **likelihood:**

$$P(w|c) = \frac{f(w,c)}{\sum_{w \in c} f(w,c)}$$

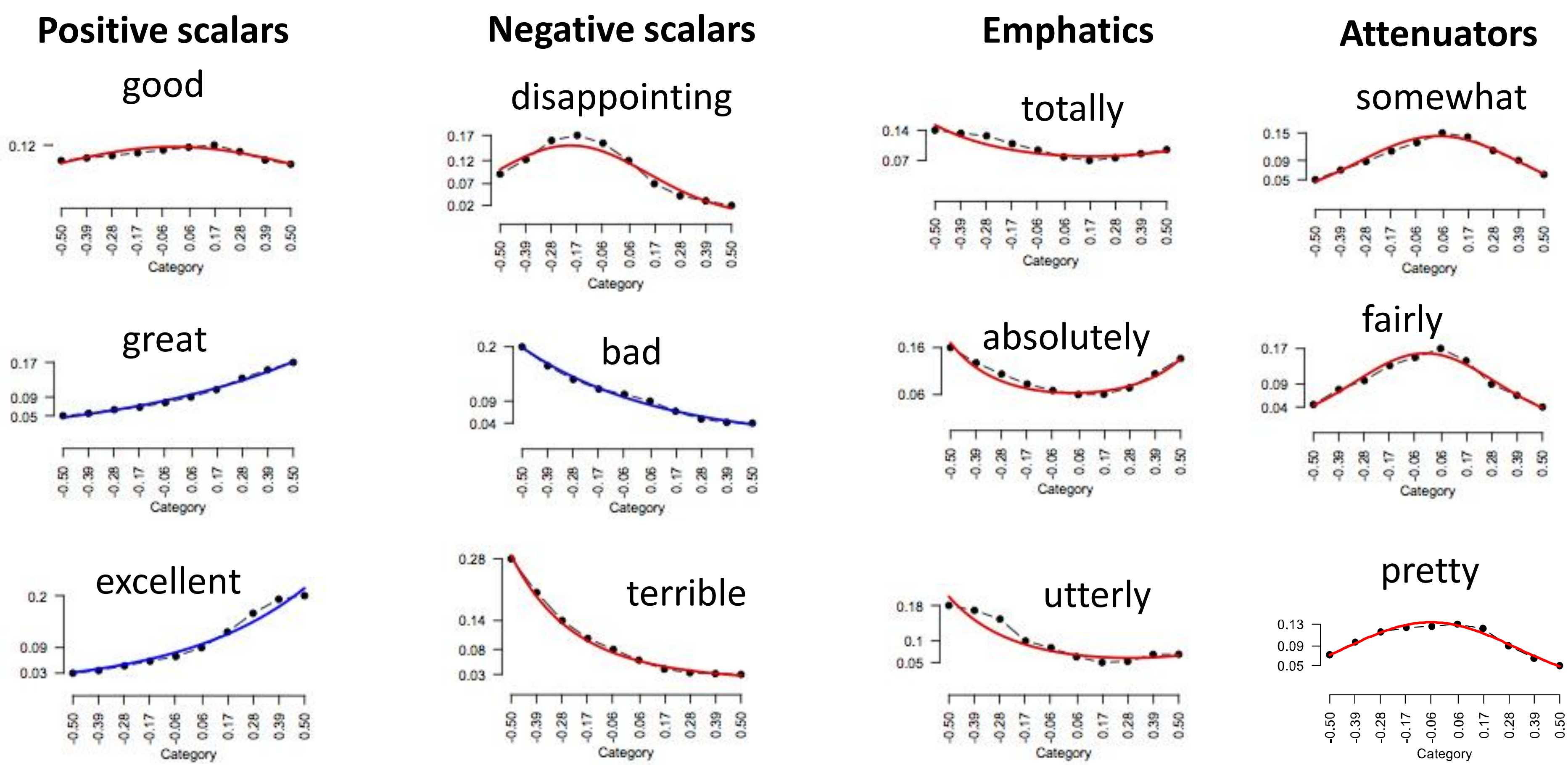
- Make them comparable between words
  - **Scaled likelihood:**

$$\frac{P(w|c)}{P(w)}$$



“Potts diagrams”

Potts, Christopher. 2011. NSF workshop on restructuring adjectives.



Using the lexicons to detect affect

(obsolete, only used as a baseline, or for extremely low computation design)

Lexicons for detecting document affect: Simplest unsupervised method

- Sentiment:
  - Sum the weights of each positive word in the document
  - Sum the weights of each negative word in the document
  - Choose whichever value (positive or negative) has higher sum
- Emotion:
  - Do the same for each emotion lexicon

Lexicons for detecting document affect: Simplest supervised method

- Build a classifier
  - Predict sentiment (or emotion, or personality) given features
  - Use “counts of lexicon categories” as a features
  - Sample features:
    - LIWC category “cognition” had count of 7
    - NRC Emotion category “anticipation” had count of 2
- Baseline
  - Instead use counts of **all** the words and bigrams in the training set
  - Only works if the training and test sets are very similar

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The Big Five Dimensions of Personality

- Extraversion vs. Introversion
  - sociable, assertive, playful vs. aloof, reserved, shy
- Emotional stability vs. Neuroticism
  - calm, unemotional vs. insecure, anxious
- Agreeableness vs. Disagreeable
  - friendly, cooperative vs. antagonistic, faultfinding
- Conscientiousness vs. Unconscientious
  - self-disciplined, organized vs. inefficient, careless
- Openness to experience
  - intellectual, insightful vs. shallow, unimaginative

Various text corpora labeled for personality of author

Pennebaker, James W., and Laura A. King. 1999. "Linguistic styles: language use as an individual difference." *Journal of personality and social psychology* 77, no. 6.

- 2,479 essays from psychology students (1.9 million words), "write whatever comes into your mind" for 20 minutes

Mehl, Matthias R, SD Gosling, JW Pennebaker. 2006. Personality in its natural habitat: manifestations and implicit folk theories of personality in daily life. Journal of personality and social psychology 90 (5), 862

- Speech from Electronically Activated Recorder (EAR)
- Random snippets of conversation recorded, transcribed
- 96 participants, total of 97,468 words and 15,269 utterances

Schwartz, H. Andrew, Johannes C. Eichstaedt, Margaret L. Kern, Lukasz Dziurzynski, Stephanie M. Ramones, Megha Agrawal, Achal Shah et al. 2013. "Personality, gender, and age in the language of social media: The open-vocabulary approach." *PloS one* 8, no. 9

- Facebook
- 75,000 volunteers
- 309 million words
- All took a personality test

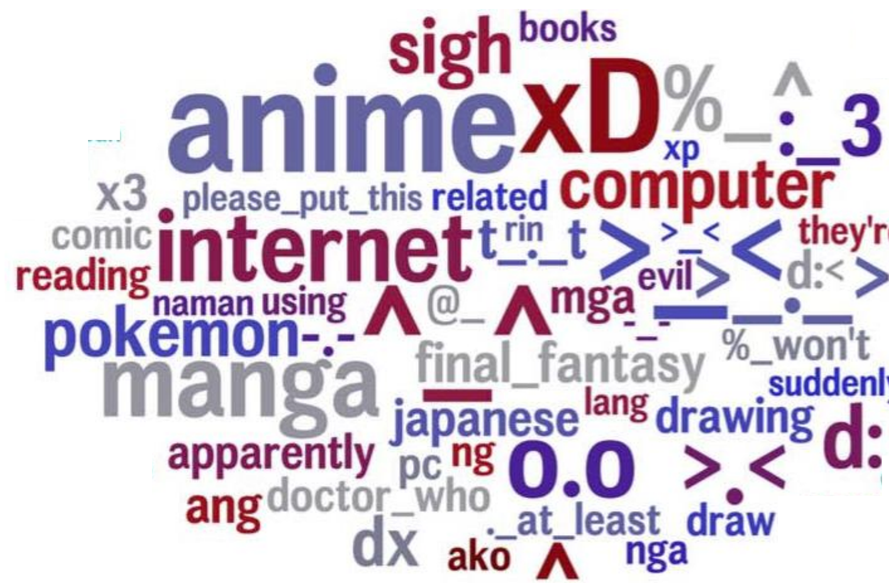
EAR (speech) corpus (Mehl et al.)

Introvert	Extravert
- Yeah you would do kilograms. Yeah I see what you're saying. - On Tuesday I have class. I don't know. - I don't know. A16. Yeah, that is kind of cool. - I don't know. I just can't wait to be with you and not have to do this every night, you know? - Yeah. You don't know. Is there a bed in there? Well ok just...	- That's my first yogurt experience here. Really watery. Why? - Damn. New game. - Oh. - That's so rude. That. - Yeah, but he, they like each other. He likes her. - They are going to end up breaking up and he's going to be like.
Unconscientious	**Conscientious**
- With the Chinese. Get it together. - I tried to yell at you through the window. Oh. xxxx's fucking a dumb ass. Look at him. Look at him, dude. Look at him. I wish we had a camera. He's fucking brushing his t-shirt with a tooth brush. Get a kick of it. Don't steal nothing.	- I don't, I don't know for a fact but I would imagine that historically women who have entered prostitution have done so, not everyone, but for the majority out of extreme desperation and I think. I don't know, i think people understand that desperation and they don't don't see [...]

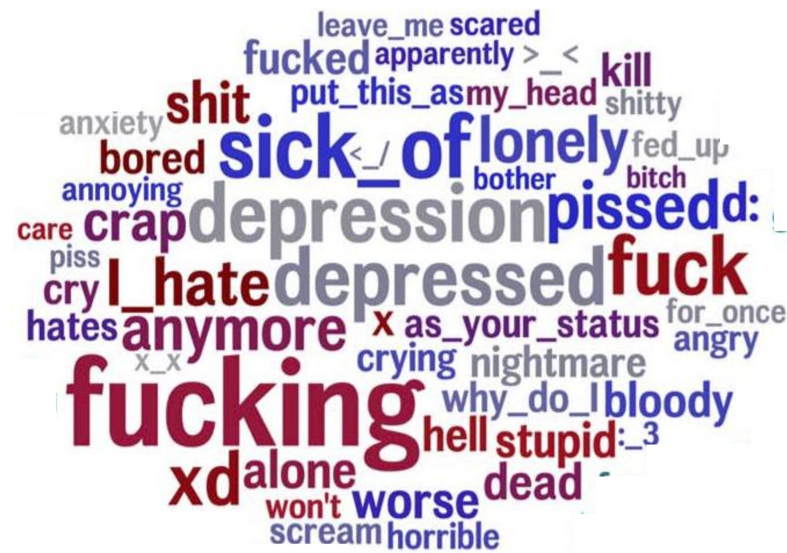
Essays corpus (Pennebaker and King)

Introvert	**Extravert**
I've been waking up on time so far. What has it been, 5 days? Dear me, I'll never keep it up, being such not a morning person and all. But maybe I'll adjust, or not. I want internet access in my room, I don't have it yet, but I will on Wed??? I think. But that ain't soon enough, cause I got calculus homework [...]	I have some really random thoughts. I want the best things out of life. But I fear that I want too much! What if I fall flat on my face and don't amount to anything. But I feel like I was born to do BIG things on this earth. But who knows... There is this Persian party today.
Neurotic	**Emotionally stable**
One of my friends just barged in, and I jumped in my seat. This is crazy. I should tell him not to do that again. I'm not that fastidious actually. But certain things annoy me. The things that would annoy me would actually annoy any normal human being, so I know I'm not a freak.	I should excel in this sport because I know how to push my body harder than anyone I know, no matter what the test I always push my body harder than everyone else. I want to be the best no matter what the sport or event. I should also be good at this because I love to ride my bike.

Facebook study, Learned words, Extraversion versus Introversion



Facebook study, Learned words
Neuroticism versus Emotional Stability



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Affect extraction: of course it's not just the lexicon

Ranganath et al (2013), McFarland et al (2014)

- Detecting interpersonal stance in conversation
- Speed dating study, 1000 4-minute speed dates
- Subjects labeled **selves** and **each other** for
    - friendly (each on a scale of 1-10)
    - awkward
    - flirtatious
    - assertive

Affect extraction: of course it's not just the lexicon

Logistic regression classifier with

- LIWC lexicons
- Other lexical features
  - Lists of hedges

  hedge: a word or phrase that makes what you say less strong (I wondered if I could have a word with you?)
- Prosody (pitch and energy means and variance)
- Discourse features
  - Interruptions
  - Dialog acts/Adjacency pairs
    - sympathy ("Oh, that's terrible")
    - clarification question ("What?")
    - appreciations ("That's awesome!")

Results on affect extraction

- Friendliness
  - -negEmotion
  - -hedge
  - higher pitch
- Awkwardness
  - +negation
  - +hedges
  - +questions

Summary: Connotation in the lexicon

- Words have various connotational aspects
- Methods for building connotation lexicons
  Based on theoretical models of emotion, sentiment
  - By hand (mainly using crowdsourcing)
  - Semi-supervised learning from seed words
  - Fully supervised (when you can find a convenient signal in the world)
- Applying lexicons to detect affect and sentiment
  - Unsupervised: pick simple majority sentiment (positive/negative words)
  - Supervised: learn weights for each lexical category

Sentiment Analysis

Positive or negative movie review?

- Unbelievably disappointing

- Full of zany characters and richly applied satire, and some great plot twists

- This is the greatest screwball comedy ever filmed

- It was pathetic. The worst part about it was the boxing scenes.

Google Product Search

HP Officejet 6500A Plus e-All-in-One Color Ink-jet - Fax / copier / printer / scanner

$89 online, **$100** nearby ★★★★☆ 377 reviews

September 2010 - Printer - HP - Inkjet - Office - Copier - Color - Scanner - Fax - 250 sh

Reviews

Summary - Based on 377 reviews

What people are saying

ease of use	"This was very easy to setup to four computers."
value	"Appreciate good quality at a fair price."
setup	"Overall pretty easy setup."
customer service	"I DO like honest tech support people."
size	"Pretty Paper weight."
mode	"Photos were fair on the high quality mode."
colors	"Full color prints came out with great quality."

Bing Shopping

HP Officejet 6500A E710N Multifunction Printer

Product summary | Find best price | **Customer reviews** | Specifications | Related items

$121.53 - $242.39 (14 stores)

☐ Compare

Average rating ★★★½☆ (144)

- ★★★★★ (55)
- ★★★★☆ (54)
- ★★★☆☆ (10)
- ★★☆☆☆ (6)
- ★☆☆☆☆ (23)
- ☆☆☆☆☆ (0)

Most mentioned

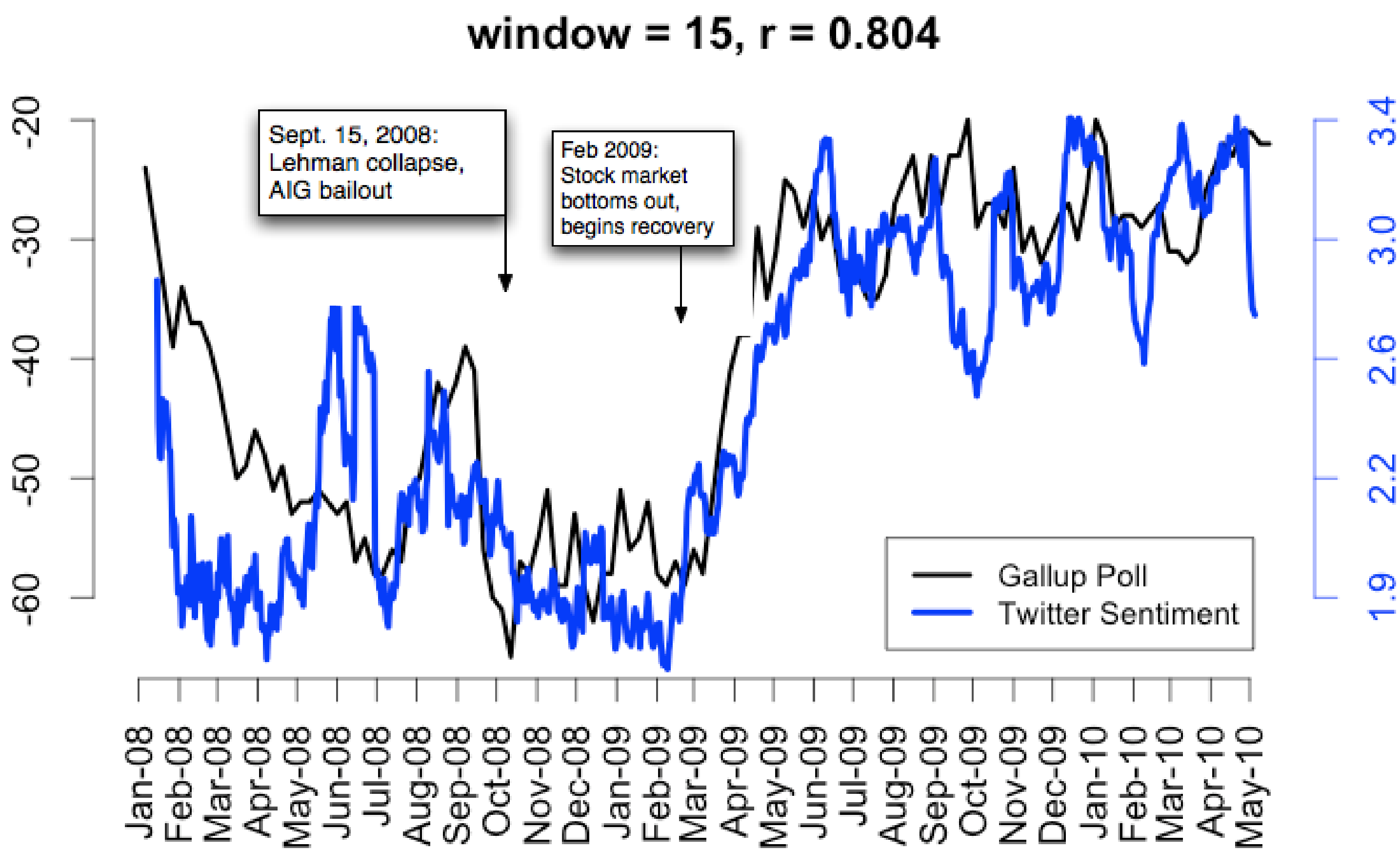
- Performance (57)
- Ease of Use (43)
- Print Speed (39)
- Connectivity (31)
- More ▼

Show reviews by source

- Best Buy (140)
- CNET (5)
- Amazon.com (3)

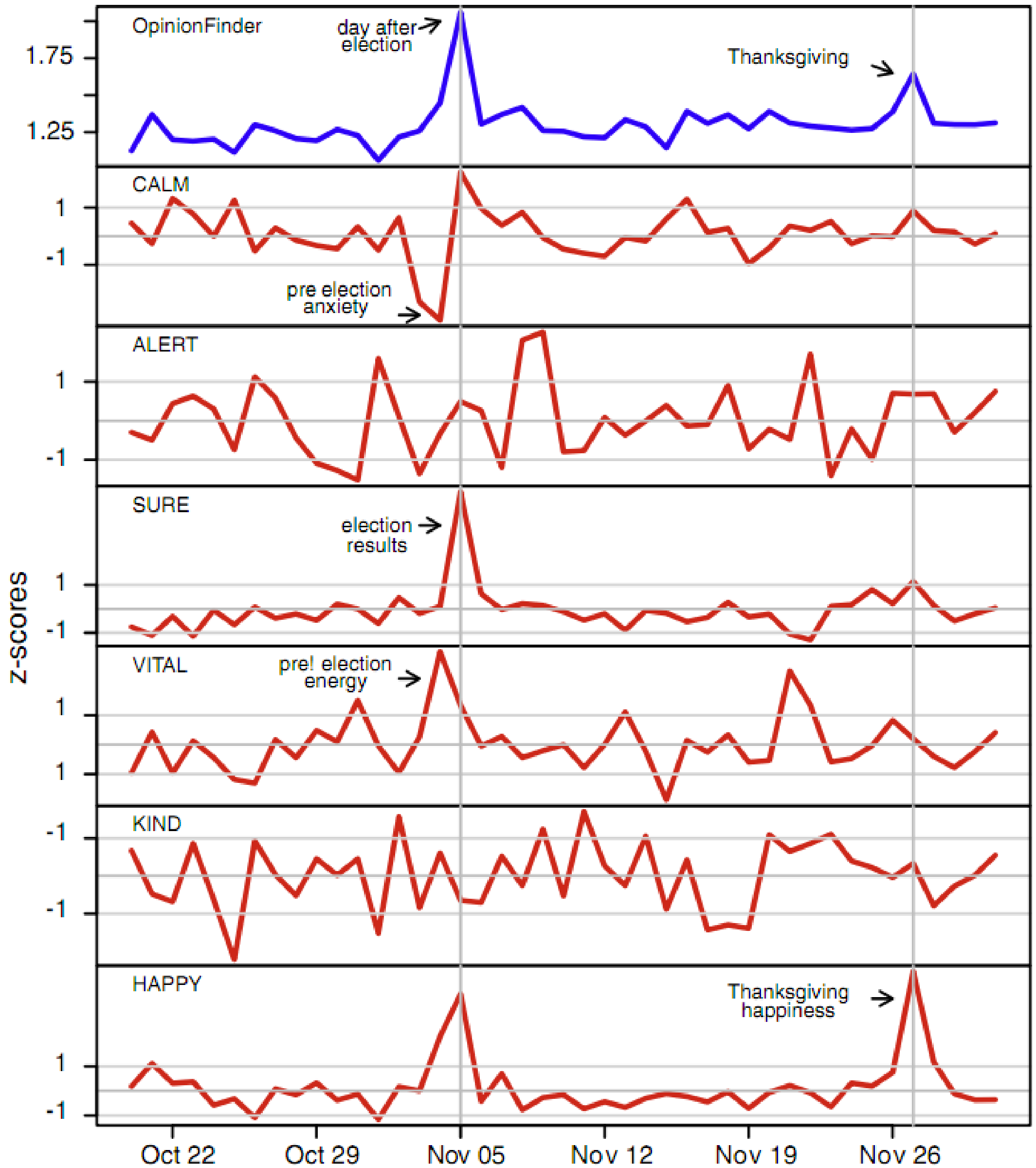
Twitter sentiment versus Gallup Poll of Consumer Confidence

Brendan O'Connor, Ramnath Balasubramanyan, Bryan R. Routledge, and Noah A. Smith. 2010. From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. In ICWSM-2010



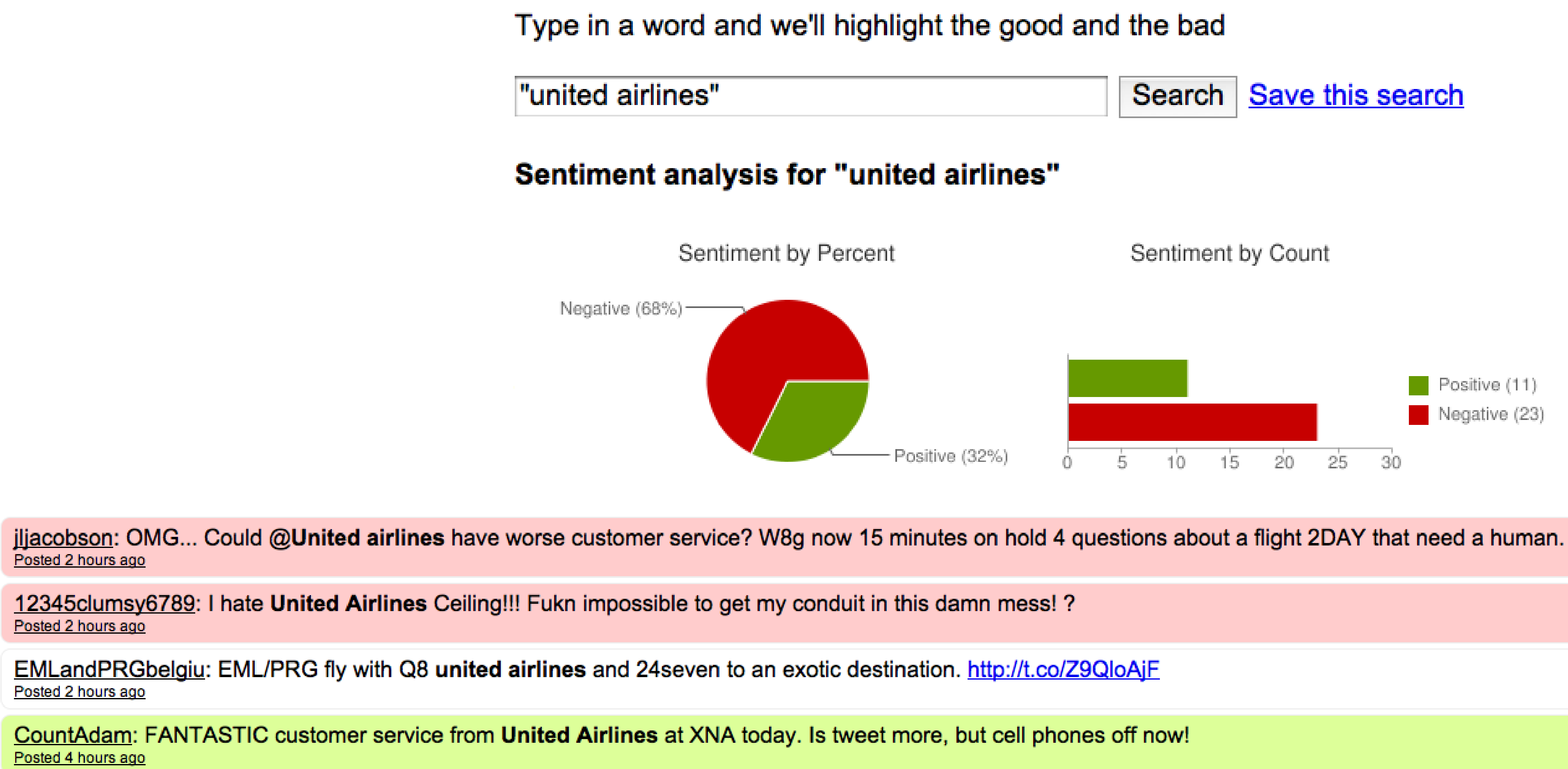
Twitter sentiment:

Johan Bollen, Huina Mao, Xiaojun Zeng. 2011. [Twitter mood predicts the stock market,](https://doi.org/10.1016/j.jocs.2010.12.007) Journal of Computational Science 2:1, 1-8. 10.1016/j.jocs.2010.12.007.



Target Sentiment on Twitter

- [Twitter Sentiment App]()
- Alec Go, Richa Bhayani, Lei Huang. 2009. Twitter Sentiment Classification using Distant Supervision



Sentiment analysis has many other names

- Opinion extraction
- Opinion mining
- Sentiment mining
- Subjectivity analysis

Why sentiment analysis?

- *Movie*: is this review positive or negative?
- *Products*: what do people think about the new iPhone?
- *Public sentiment*: how is consumer confidence? Is despair increasing?
- *Politics*: what do people think about this candidate or issue?
- *Prediction*: predict election outcomes or market trends from sentiment

Scherer Typology of Affective States

- **Emotion**: brief organically synchronized … evaluation of a major event
  - *angry, sad, joyful, fearful, ashamed, proud, elated*
- **Mood**: diffuse non-caused low-intensity long-duration change in subjective feeling
  - *cheerful, gloomy, irritable, listless, depressed, buoyant*
- **Interpersonal stances**: affective stance toward another person in a specific interaction
  - *friendly, flirtatious, distant, cold, warm, supportive, contemptuous*
- **Attitudes: enduring, affectively colored beliefs, dispositions towards objects or persons**
  - *liking, loving, hating, valuing, desiring*
- **Personality traits**: stable personality dispositions and typical behavior tendencies
  - *nervous, anxious, reckless, morose, hostile, jealous*

Sentiment Analysis

- Sentiment analysis is the detection of **attitudes**

  "enduring, affectively colored beliefs, dispositions towards objects or persons"

  1. **Holder (source)** of attitude
  2. **Target (aspect)** of attitude
  3. **Type** of attitude
     - From a set of types
       - *Like, love, hate, value, desire,* etc.
     - Or (more commonly) simple weighted **polarity**:
       - *positive, negative, neutral,* together with *strength*
  4. **Text** containing the attitude
     - Sentence or entire document

Sentiment Analysis

- Simplest task:
  - Is the attitude of this text positive or negative?
- More complex:
  - Rank the attitude of this text from 1 to 5
- Advanced:
  - Detect the target, source, or complex attitude types

Sentiment Analysis

- Simplest task:
  - Is the attitude of this text positive or negative?
- More complex:
  - Rank the attitude of this text from 1 to 5
- Advanced:
  - Detect the target, source, or complex attitude types

Sentiment Classification in Movie Reviews

Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.
Bo Pang and Lillian Lee. 2004. A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts. ACL, 271-278

- Polarity detection:
  - Is an IMDB movie review positive or negative?
- Data: *Polarity Data 2.0:*
  - http://www.cs.cornell.edu/people/pabo/movie-review-data

IMDB data in the Pang and Lee database

✓

when _star wars_ came out some twenty years ago , the image of traveling throughout the stars has become a commonplace image . […]

when han solo goes light speed , the stars change to bright lines , going towards the viewer in lines that converge at an invisible point .

cool .

october sky offers a much simpler image–that of a single white dot , traveling horizontally across the night sky . [. . .]

✗

“ snake eyes ” is the most aggravating kind of movie : the kind that shows so much potential then becomes unbelievably disappointing .

it’s not just because this is a brian depalma film , and since he’s a great director and one who’s films are always greeted with at least some fanfare .

and it’s not even because this was a film starring nicolas cage and since he gives a brauvara performance , this film is hardly worth his talents .

Sentiment Tokenization Issues

- Deal with HTML and XML markup
- Twitter mark-up (names, hash tags)
- Capitalization (preserve for words in all caps)
- Phone numbers, dates
- Emoticons

Problems: What makes reviews hard to classify?

- Subtlety:
  - Perfume review in *Perfumes: the Guide*:
    - "If you are reading this because it is your darling fragrance, please wear it at home exclusively, and tape the windows shut."
  - Dorothy Parker on Katherine Hepburn
    - "She runs the gamut of emotions from A to B"

Thwarted Expectations and Ordering Effects

- "This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it **can't hold up**."
- Well as usual Keanu Reeves is nothing special, but surprisingly, the very talented Laurence Fishbourne is **not so good** either, I was surprised.

Sentiment analysis in Slovene

- lexicon based on Bing Liu (2004), KSS
- a few other lexicons
- a few annotated datasets (tweets, user commentaries)
- SentiCoref, aspect based datasets (including coreferences)

KADUNC, Klemen, ROBNIK ŠIKONJA, Marko. Analiza mnenj s pomočjo strojnega učenja in slovenskega leksikona sentimenta. V *Zbornik konference Jezikovne tehnologije in digitalna humanistika,* 2016, str. 83-89, http://nl.ijs.si/jtdh16/JTDH-2016-Proceedings.pdf.

Sentiment lexicons

- the most useful in English
  Hu & Liu (2004), later updated,
  2,006 positive and
  4,783 negative words

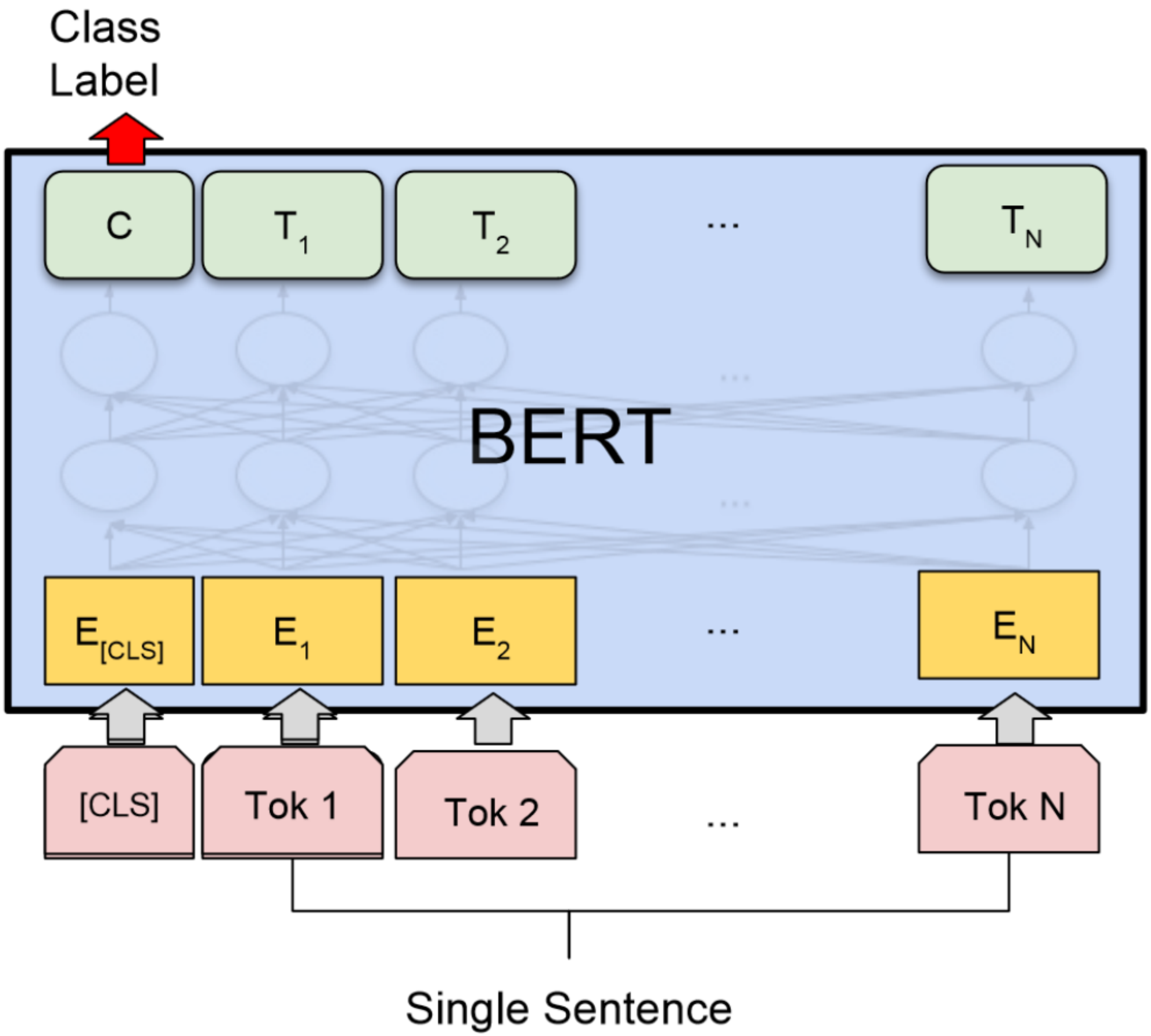
positive words	negative words
a+	2-faced
abound	2-faces
abounds	abnormal
abundance	abolish
abundant	abominable
accessable	abominably
…	…

- in Slovene:
  - Rok Martinc (2013), based on AFINN-111 list (Nielsen, 2011), contains 2,477 words, estimated in range, -5…+5
  - Mateja Volčanšek (2015), based on General Inquirer (Stone, 1997), 1,669 positive and 1,912 negative words
  - Klemen Kadunc (2016), based on Hu & Liu

Standard and neural approaches

- standard ML approaches, using standard pipelines
  - classification accuracy between 60% and 70%
- neural approaches
  - a few percent more

Sentence classification using BERT – sentiment



Cross-lingual approach

- Dataset: Twitter sentiment dataset in 13 languages

	Number of tweets				Agreement ($\overline{F_1}$)	
Language	Negative	Neutral	Positive	All	Self-	Inter-
Bosnian	12,868	11,526	13,711	38,105	0.78	-
Bulgarian	15,140	31,214	20,815	67,169	0.77	0.50
Croatian	21,068	19,039	43,894	84,001	0.83	-
English	26,674	46,972	29,388	103,034	0.79	0.67
German	20,617	60,061	28,452	109,130	0.73	0.42
Hungarian	10,770	22,359	35,376	68,505	0.76	-
Polish	67,083	60,486	96,005	223,574	0.84	0.67
Portuguese	58,592	53,820	44,981	157,393	0.74	-
Russian	34,252	44,044	29,477	107,773	0.82	-
Serbian	24,860	30,700	16,161	71,721	0.46	0.51
Slovak	18,716	14,917	36,792	70,425	0.77	-
Slovene	38,975	60,679	34,281	133,935	0.73	0.54
Swedish	25,319	17,857	15,371	58,547	0.76	-

Robnik-Šikonja, M., Reba, K. and Mozetič, I., 2021. Cross-lingual transfer of sentiment classifiers. Slovenščina 2.0: empirical, applied and interdisciplinary research, 9(1), pp.1-25.

Cross-lingual representation

1. projection of 93 languages into a joint embedding space (LASER library), using a parallel corpora with either English or Spanish match
   - embeddings, MLP layer with 8 neurons, followed by an output layer with 3 neurons (3 classes)
   - ReLU activation function, Adam optimizer
   - batch size 32, 10 epochs.
2. multilingual BERT, trained on 104 languages
3. CroSloEngual BERT, trained on Croatian, English and Slovene
   - fine-tuning both BERT models

XL transfer between similar languages

- reporting the classification accuracy and average F_1 score over positive and negative class

Source	Target	LASER $\overline{F}_1$	LASER CA	mBERT $\overline{F}_1$	mBERT CA	CSE BERT $\overline{F}_1$	CSE BERT CA	Both target $\overline{F}_1$	Both target CA
German	English	0.55	0.59	**0.63**	**0.64**	0.42	0.42	0.62	0.65
English	German	0.55	0.60	**0.66**	**0.70**	0.50	0.58	0.53	0.65
Polish	Russian	**0.64**	**0.59**	0.57	0.57	0.50	0.40	0.70	0.70
Polish	Slovak	**0.63**	0.59	0.58	0.59	**0.63**	**0.65**	0.72	0.72
German	Swedish	0.58	0.57	**0.59**	**0.59**	0.58	0.56	0.67	0.65
German Swedish	English	**0.58**	**0.60**	0.55	0.56	0.41	0.42	0.62	0.65
Slovene Serbian	Russian	0.53	0.55	0.57	**0.57**	**0.58**	0.48	0.70	0.70
Slovene Serbian	Slovak	**0.59**	0.52	0.57	0.59	0.48	**0.60**	0.72	0.72
Serbian	Slovene	0.54	**0.57**	0.54	0.54	**0.56**	0.55	0.60	0.60
Serbian	Croatian	**0.67**	0.64	0.65	0.62	0.65	**0.70**	0.73	0.68
Serbian	Bosnian	**0.65**	0.61	0.61	0.60	0.59	**0.62**	0.67	0.64
Polish	Slovene	0.51	0.48	**0.55**	**0.54**	0.50	0.53	0.60	0.60
Slovak	Slovene	0.52	0.51	0.54	0.54	**0.58**	**0.58**	0.60	0.60
Croatian	Slovene	0.53	0.53	0.53	0.54	**0.61**	**0.60**	0.60	0.60
Croatian	Serbian	**0.54**	**0.52**	0.52	0.51	0.52	0.49	0.48	0.54
Croatian	Bosnian	0.66	0.61	0.57	0.56	**0.67**	**0.62**	0.67	0.64
Slovene	Croatian	0.70	0.65	0.64	0.63	**0.73**	**0.69**	0.73	0.68
Slovene	Serbian	**0.52**	**0.55**	0.46	0.49	0.47	0.50	0.48	0.54
Slovene	Bosnian	**0.66**	0.61	0.58	0.56	**0.66**	**0.62**	0.67	0.64
Average performance gap		0.05	0.07	0.06	0.07	0.08	0.08		

Source	Target	LASER $\overline{F}_1$	LASER CA	mBERT $\overline{F}_1$	mBERT CA	CSE BERT $\overline{F}_1$	CSE BERT CA	Both target $\overline{F}_1$	Both target CA
Croatian	Slovene	0.53	0.53	0.53	0.54	**0.61**	**0.60**	0.60	0.60
Croatian	English	**0.63**	0.63	**0.63**	**0.66**	0.62	0.64	0.62	0.65
English	Slovene	0.54	0.57	0.50	0.53	**0.59**	**0.57**	0.60	0.60
English	Croatian	0.62	**0.67**	0.67	0.63	**0.73**	**0.67**	0.73	0.68
Slovene	English	0.63	0.64	**0.65**	**0.67**	0.63	0.64	0.62	0.65
Slovene	Croatian	0.70	0.65	0.64	0.63	**0.73**	**0.69**	0.73	0.68
Croatian English	Slovene	0.54	0.54	0.53	0.54	**0.60**	**0.58**	0.60	0.60
Croatian Slovene	English	0.62	0.61	**0.65**	**0.67**	0.63	0.65	0.62	0.65
English Slovene	Croatian	0.64	0.68	0.63	0.63	**0.68**	**0.70**	0.73	0.68
Average performance gap		0.04	0.03	0.04	0.03	0.00	0.01		

Expansion of the training set with other languages

- unsuccessful if the dataset is large enough (as in the case shown)

	LASER				mBERT			
	All & Target		Only Target		All &Target		Only Target	
Target	$\bar{F}_1$	CA	$\bar{F}_1$	CA	$\bar{F}_1$	CA	$\bar{F}_1$	CA
Bosnian	0.64	0.59	0.67	0.64	0.63	0.60	0.65	0.60
Bulgarian	**0.54**	0.56	0.50	0.59	**0.60**	**0.60**	0.58	0.59
Croatian	0.63	0.57	0.73	0.68	**0.65**	0.63	0.64	0.66
English	0.58	0.60	0.62	0.65	0.64	**0.69**	0.68	0.68
German	0.52	0.59	0.53	0.65	0.61	0.66	0.66	0.66
Hungarian	0.59	0.61	0.60	0.67	0.65	0.69	0.65	0.69
Polish	0.67	0.63	0.70	0.66	**0.71**	**0.71**	0.70	0.70
Portuguese	0.44	0.39	0.52	0.51	**0.52**	**0.52**	0.50	0.49
Russian	0.66	0.64	0.70	0.70	**0.67**	**0.66**	0.64	0.64
Serbian	**0.52**	0.49	0.48	0.54	**0.53**	0.51	0.50	0.52
Slovak	0.64	0.61	0.72	0.72	0.67	0.65	0.67	0.66
Slovene	0.54	0.50	0.60	0.60	0.56	0.54	0.58	0.58
Swedish	0.63	0.59	0.67	0.65	0.67	0.64	0.67	0.65
Avg. gap	0.03	0.06			0.00	0.00		

Comparison of representations: LASER, mBERT, CSE BERT and SVM

Language	LASER		mBERT		CSE BERT		SVM		Majority
	$\overline{F_1}$	CA	$\overline{F_1}$	CA	$\overline{F_1}$	CA	$\overline{F_1}$	CA	CA
Bosnian	**0.68**	0.64	0.65	0.60	**0.68**	**0.65**	(0.61	0.56)	0.36
Bulgarian	0.53	**0.59**	**0.58**	**0.59**	0.00	0.45	0.52	0.54	0.46
Croatian	0.72	0.68	0.64	0.66	**0.76**	**0.71**	(0.61	0.56)	0.52
English	0.62	0.65	**0.68**	**0.68**	0.67	0.66	0.63	0.64	0.44
German	0.52	0.64	**0.66**	**0.66**	0.31	0.59	0.54	0.61	0.53
Hungarian	0.63	0.67	**0.65**	**0.69**	0.57	0.65	0.64	0.67	0.53
Polish	**0.70**	0.66	**0.70**	**0.70**	0.56	0.57	0.68	0.63	0.44
Portuguese	0.48	0.47	0.50	0.49	0.12	0.22	**0.55**	**0.51**	0.37
Russian	**0.70**	**0.70**	0.64	0.64	0.07	0.43	0.61	0.60	0.40
Serbian	0.50	0.54	0.50	0.52	0.30	0.50	(**0.61**	**0.56**)	0.43
Slovak	**0.72**	**0.72**	0.67	0.66	0.69	0.71	0.68	0.68	0.52
Slovene	0.57	0.58	0.58	0.58	**0.60**	**0.61**	0.55	0.54	0.43
Swedish	**0.67**	0.64	**0.67**	**0.65**	0.54	0.56	0.66	0.62	0.43
#Best	5	3	6	6	3	3	2	2	0
Average	0.62	0.63	0.62	0.62	0.45	0.56	0.61	0.60	0.45

Related task: aspect-based sentiment detection

- aspect-based (also targeted) sentiment detection
  - fixed aspects, e.g., product properties, persons or companies
  - automatically detected aspects, e.g., side effects in drug reviews
- example:
  We had a great experience at the restaurant, food was delicious, but the service was kinda bad.
  - aspect “service”, label “negative
  - aspect “food”, label “positive”.

Related task: depression detection from text

- Datasets
  - Reddit dataset (Kayalvizhi and Thenmozhi, 2022) with posts from the Reddit social platform, mostly from subreddits “r/stress”, “r/loneliness”, “r/Anxiety”, “r/depression” etc. , 13,000 posts, 3 levels
  - Twitter dataset (Hu, 2021), 66,000 labelled tweets, 4 levels
- baselines: majority, TF-IDF, Doc2Vec
- BERT models: BERT, RoBERTa, mentalBERT, BERTweet
- ensembles: averaging, Bayesian
- hyperparameter tuning
- relatively small differences between models
- successful transfer from Reddit to Twitter but not reverse

- Tavchioski, I., Robnik-Šikonja, M. and Pollak, S., Detection of depression on social networks using transformers and ensembles. *Proceedings of 10th Language & Technology Conference: Human Language Technologies as a Challenge for Computer Science and Linguistics, LTC 2023*, pages 282-287

Related tasks: detection of hate speech, offensive speech, socially unacceptable speech,patronizing and condescending speech

- These categories are related to sentiment and emotion analysis but also differ in some aspects, e.g., lexicon. Intention, subtlety
- Approach: find a suitable dataset for SFT (supervised finetuning) of BERT models or LLMs
- Raw LLMs with prompting mostly lag behind finetuned models

Some recent scores

TABLE VI: Macro F_1 scores on sentiment prediction and offensive language prediction detection tasks achieved with massively multilingual, few-lingual, monolingual, and generative models across five primary languages. The best F_1 score for each language is displayed in **bold**.

(a) Results on Slovene datasets.

Model	Sentiment Analysis	Offensive Language Prediction
mBERTc-base	0.617	0.785
XLM-R-base	0.645	0.811
TwHIN-BERT-base	0.619	0.808
SlEng-BERT*	**0.666**	**0.850**
SloBERTa-SlEng*	0.659	0.845
CroSloEngual BERT	0.660	0.834
SloBERTa	0.650	0.840
GPT-3	0.597	0.825
LlaMa-3.1-8B	0.603	0.849

YADAV, Anjali, GARG, Tanya, KLEMEN, Matej, ULČAR, Matej, AGARWAL, Basant, ROBNIK ŠIKONJA, Marko. From translation to generative LLMs: classification of code-mixed affective tasks. IEEE transactions on affective computing. 2025, DOI: 10.1109/TAFFC.2025.3553399